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The optimal research and development portfolio of low-carbon energy technologies: A study of China

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ABSTRACT

To support decision-making for an optimal portfolio strategy for low-carbon energy technology research and development (R&D), this study proposes a dynamic two-stage stochastic programming model, taking into account both the uncertainty of technological change and damages of climate change. Based on China's economic and technology level and expert elicitation, an R&D investment portfolio strategy looking at three low-carbon technologies (carbon capture and storage [CCS], solar photovoltaic [PV], and nuclear), including nine projects, is investigated through the proposed model. The optimized results show that the optimal R&D technology portfolio is robust to different levels of risk in climate damage. However, the total social costs for the optimal R&D technology portfolio is lowest in the medium risk of climate damage scenario. Under different opportunity costs, the composition of the optimal R&D portfolio varies. However, projects for each of the three technologies always constitute the optimal R&D portfolio. Furthermore, the implication is that a technology synergistic R&D strategy is conducive to enhancing the level of CO_2 abatement and reducing the total social cost.

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1. Introduction

Climate change has become one of the most important issues in the world. Increasing GHG emissions in the atmosphere caused by human activity, such as fossil fuel combustion, has been identified as a primary cause of ongoing climate change (IPCC, 2014). Although the growth in global GHG emissions has slowed in the last two years (Peters et al., 2017), the issue of climate change remains a critical challenge based on the longevity of its effects, its global nature, and deep uncertainty. Some measures have proven to be effective in reducing energy-related GHG emissions, including improving the efficiency of energy use and the development of carbon-free renewable energy, and adjustment the industrial structure of high fossil fuel consumption and high carbon-based. However, no matter which method is chosen, a rapid change to low-carbon energy is necessary to inhibit climate change in a way that is consistent with sustainable economic growth and current policies (Blanford, 2009; Wang et al., 2018; Yu et al., 2015). The innovation of new clean technologies has also become a focus of discussion in recent negotiation on climate change (Suzuki, 2015). In general, learning by doing and investment in research and development (R&D) are two basic ways to achieve technological change. Learning by doing provides some insights, but has key weaknesses and requires information about past performance. Since many of the technologies do not yet exist in commercial form, there is no past performance on which to base an estimate (Nordhaus, 2009). Moreover, learning by doing usually takes a long time to achieve a technology breakthrough as it is based on the experience of the production and natural diffusion of technologies. Therefore, it is difficult to cope with the severe challenges of global warming. On the other hand, R&D can have a significant effect on improving the performance of low-carbon energy technologies (Barron and McJeon, 2015; Hellsmark et al., 2016) and has been found to be cost-effective (Corderi and Lin, 2011). Moreover, the development of new technologies and the improvement of existing ones can enhance policy responses to challenges like climate change.

Several analyses of the role of investment in R&D have been conducted, with each focusing on a single group of low-carbon energy technologies to assess climate change impacts. By

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combining expert elicitations and economic modeling, the impact on climate change of R&D in individual technology has been investigated in areas such as solar photovoltaic (Baker et al., 2009a), carbon capture and storage (CCS) (Baker et al., 2009b; Nemet et al., 2015), nuclear power (Baker et al., 2008), automobile batteries (Baker et al., 2010), and boiler technologies (Park et al., 2017). These studies have shown that the availability of the technology plays a vital role in feasibility and cost when facing the challenge of stringent climatic targets. However, this individual technology research limits the insights that such studies can offer about the interdependencies among technologies. Multi-technology assessments can address environmental and technological interdependency issues (Barron, 2015). The technology portfolios are powerful tools in that they allow R&D projects to be analyzed in a systematic manner (Cluzel et al., 2016). Therefore, when constrained by a given budget and facing a set goal of carbon emissions targets, it is critical to make a decision on the R&D strategy for a portfolio of low-carbon energy technologies. However, in such a discussion, it is not clear what technologies the portfolio should contain.

A strategy for an R&D portfolio of technologies involves significant uncertainty, which cannot be avoided. Technology breakthrough requires risky efforts in R&D because of its high uncertainty and capital intensiveness (Arvanitis et al., 2017; Marangoni et al., 2017). For example, for a particular R&D program, success or failure is uncertain, and the degree the program will meet or exceed the set goals is also uncertain. Furthermore, there is a significant uncertainty that experts attach to R&D investments as well as huge disagreement among such experts (Baker et al., 2015a; Marangoni et al., 2017). A number of researchers have developed various models to deal with a portfolio strategy for R&D technologies taking into account uncertainty. Among them, the integrated assessment model (IAM) is the most common approach to dealing with uncertainty within portfolio optimization. For instance, by running an IAM, Blanford (2009) calculated the optimal portfolio by linking R&D investments to a probability distribution over alternative outcomes. Lemoine and Traeger (2014) evaluated optimal climate policies in a dynamic integrated model of climate and the economy (DICE), a widely accepted IAM, including the endogenous possibility of climatic tipping points, their welfare implications, and learning their trigger temperatures. Through a large IAM, Baker et al. (2015b) estimated the economic interactions of five technologies, considering four sets of probabilistic distributions from experts. Beyond the IAM, other types of energy-economic models have also been proposed to obtain an optimal R&D portfolio of low-carbon energy technologies. For instance, Bistline (2016) developed a stochastic R&D portfolio management framework to determine the optimal investment levels for individual programs subject to a budget constraint, using an empirically grounded model of R&D-driven innovation with uncertain returns. Based on the MARket ALlocation (MARKAL) model, Chan and Anadon (2016) proposed a sampling and optimization strategy to calculate optimal R&D portfolios by evaluating different metrics (such as system benefits, technology diffusion, and uncertainty around outcomes) relevant to an energy R&D portfolio. Within the framework of a bottom-up partial equilibrium model, Usui et al. (2017) investigated the dynamic technology transition in the Japanese electricity sector and the optimized R&D investment schedule for each renewable. These studies have focused on the uncertainties of low-carbon energy technologies themselves and the uncertainties of their R&D outcomes but have not included the uncertainties of damage caused by climate change. The potential damages from climate change are also deeply uncertain; in particular, how will an extra ton of carbon emitted today impact a stream of damage in the future (Baker and Solak, 2011)? The marginal damage of climate change is critical to climate policy formulation. Further, the damage degree of climate change (degree of risk) can also affect technological change (Baker and Shittu, 2008; Bistline and Weyant, 2013; Yu et al., 2017).

Therefore, recently, several studies have explored the optimal R&D portfolio of low-carbon energy technology, taking into account the uncertainty of both technological change and damages caused by climate change. For example, considering the uncertainty of future technological success and climate change, Baker and Solak (2014) investigated an R&D portfolio of US energy technologies (nuclear, solar PV, and CCS). They found that the optimal technology portfolio was fairly robust to different specifications of climate uncertainty. Similarly, Barron et al. (2014) examined the impact of US grid integration costs on the optimal R&D portfolio that minimized the cost of climate change. Their findings implied that the importance of getting grid integration costs right depended on the specific question being asked. By considering uncertainty in technology improvement and climate damages, Olaleye (2016) proposed a multi-model framework to determine the optimal allocation of R&D funds to a technology portfolio in the US. The general view of these studies suggests that the optimal portfolio of R&D technology mainly depends on how the modeling of the technology changes based on assumptions and data. However, these studies are all focused on a combination of low-carbon energy technologies in the US. No research investigates the investment decisions for a portfolio of R&D technology in China.

As the world's largest carbon emitter, China is facing enormous pressure to reduce emissions. Yet, China's low-carbon energy technology is lagging behind the developed countries. Therefore, considering the level of China's energy technology and carbon emissions, it is important that an optimal R&D portfolio strategy for low-carbon energy technology be studied in China as well. First, such a study would help clarify the relationship between various low-carbon energy technologies and the costs and effects of carbon emissions reduction in China. Second, obtaining the optimal investment portfolio would provide the support needed for decisions regarding formulating R&D investments while considering the committed emissions goal of re-education.

Regarding these, in the present study, we focus on China's low-carbon energy technology R&D portfolio for the first time, taking into account the uncertainty of technological change and of climate change damage. In our study, the carbon abatement cost function and climate damage cost function are introduced to characterize technological change and climate change, respectively. Furthermore, based on the expert elicitations, a two-stage stochastic model is developed to cope with the uncertainty of technological change and of climate change damage. According to the results of the modeling, we try to answer, for given budget constraints, how should the government's investment funds be allocated to different R&D projects? In other words, what is the optimal R&D technology portfolio?

The contributions of our study are as follows: First, parameter settings take full account of China's economic and technological level. For example, compared with the US, China needs more investment in CCS R&D based on a difference in technical advancement. Second, by simultaneously considering the uncertainties of technology breakthrough and climate damage, a budget constrained model (BCM) and an overall optimal model (OOM) are developed to solve the optimal portfolio of R&D technologies for a given budget and the minimized expected social cost, respectively. Finally, the swarm intelligent optimization solver, MIDACO (mixed integer distributed ant colony optimization), is applied to solve the proposed models, which can simply and efficiently obtain the solutions without many mathematical transformations.

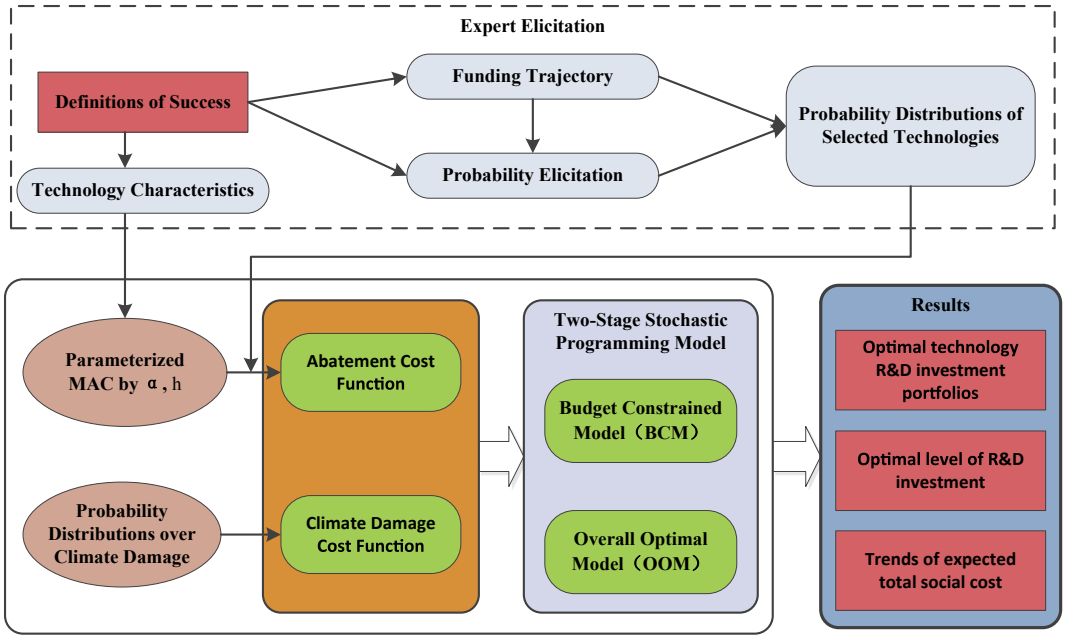

Fig. 1. Optimized model structure of low-carbon technology R&D portfolio.

2. Methodology

2.1. The model's framework and selected technologies

This study aims to minimize the total social cost of CO_2 abatement by optimizing investment in a low-carbon energy technology R&D portfolio. Based on expert elicitation, technological change is modeled as the impact on marginal abatement cost (MAC) — the cost of reducing emissions by an additional ton. To represent climate change, a climate damage cost function is introduced at the same time. Then, a two-stage stochastic programming model is developed to solve the problems mentioned above. The model structure is displayed in Fig. 1.

In the field of electricity generation, some low-carbon technologies, like biomass, solar PV, nuclear power, wind, hydrogen, and CCS, are expected to be widely applied in the future. This study mainly explores the optimal R&D investment portfolio of low-carbon energy technologies. In terms of research object, we focus on uncertainty, and then consider the technologies that have the possibility of a breakthrough and a promising future. Therefore, we do not consider technologies, such as hydro, that are relatively mature and have little uncertainty in terms of technological change. Neither do we consider biomass and wind due to a lack of data in China. As a result, CCS, solar PV, and nuclear are the focus in this study. Further, we consider three main categories of each technology. Thus, nine projects are considered, listed in Table 1.

2.2. The cost function of carbon emissions reduction

The total cost of carbon abatement is closely related to the MAC. When the MAC decreases, it shows that, compared to the past, the current level of abatement is higher, or, for the same abatement level, the abatement cost is less. The impact of low-carbon technology on the MAC varies for different technologies. In general, low-carbon technology impacts the MAC in two ways: pivot and shift. The former changes the slope of the MAC curve, while the latter changes the intercept of the MAC curve. When the MAC is combined with marginal damages (the damages caused by reducing or increasing emissions by an additional ton), it determines the optimal abatement level (Baker et al., 2009a). In Fig. 2, we illustrate how the impact of technological change on optimal abatement varies with technology and marginal damages. The solid upward sloping line represents the original MAC, denoted by the MAC base. The two dashed lines represent different types of technological change, denoted by the MAC pivot and MAC shift. The two horizontal lines represent the level of marginal damages, denoted by low MD and high MD. The horizontal axis represents the abatement, and the vertical axis represents marginal damage or marginal cost. Note that the abatement level increased after the technological impact. When MD is low, the abatement level of the MAC shift curve is slightly higher than that of the MAC pivot curve. However, when MD is high, the difference between the two types of technological change is great. Thus, the technology advancement has an important impact on the MAC. Meanwhile, climate damage will affect the choice of technology.

The global change assessment model (GCAM)[1] can be applied to estimate the relationship between technological change and the impacts on the MAC. After successful technological change, the MAC can be expressed as:

$$\overline{MAC}(\mu;\alpha,h) = (1-\alpha)[MAC(\mu) - hMAC(0.5)] \quad (1)$$

where $\mu(\mu \in [0,1])$ represents the level of abatement, $MAC(\mu)$ represents the original MAC before technological change, α represents pivot, h represents shift, $\overline{MAC}(\mu;\alpha,h)$ represents the MAC parameterized by α and h after technological change, and $MAC(0.5)$ represents a 50% abatement of the MAC. In terms of combinations of technologies, we use Barron et al. (2014), Baker and Peng (2012) and Baker and Solak (2011) for reference; the shift is fitted by the data calculated by the GCAM; the pivot is represented by a multiplication combination of the individual technologies:

[1] The GCAM is a global integrated assessment model for climate, economy, energy, and land-use developed and maintained by the Joint Global Change Research Institute.

Table 1
Introduction of nine R&D projects.

Technology	Project	Description
CCS	Pre-combustion carbon capture (Pre-C)	Works in conjunction with combined cycle power plants to remove CO_2 from syngas generated from fossil fuels or biomass, resulting in a stream of hydrogen to be used for combustion.
	Post-combustion carbon capture (Post-C)	Removes CO_2 from flue gases, through several possible means: membranes, solvents, stimulus or cryogenic methods
	Oxyfuel (Oxy)	Use pure oxygen for combustion results in a flue gas that is almost entirely CO_2 and H_2O, thus requires almost no additional energy to separate out CO_2.
Solar PV	Organic Solar cells (Org S)	Use thin films of purely organic semiconductors such as phenyl-C61-butyric acid methyl ester.
	Inorganic Thin-film Solar cells (Thin S)	Use inorganic thin film materials beyond cadmium telluride and copper indium gallium selenide.
	Multi-junction Solar cells (Multi S)	The third generation very high efficiency solar cells, with multiple p–n junctions made of different semiconductor materials. They can produce multiple excitons for each photon received.
Nuclear	Light water reactors (LWR)	A type of thermal-neutron reactor that use normal water, as opposed to heavy water, represent a high-probability, more incremental technology.
	High temperature reactors (HTR)	Be named for their high temperature at the core outlet (usually 850–1000 °C above) and the use of nitrogen as coolant.
	Fast breeder reactors (FBR)	Operate as "breeder" reactors in a fast neutron spectrum, in which they produce more plutonium than they consume.

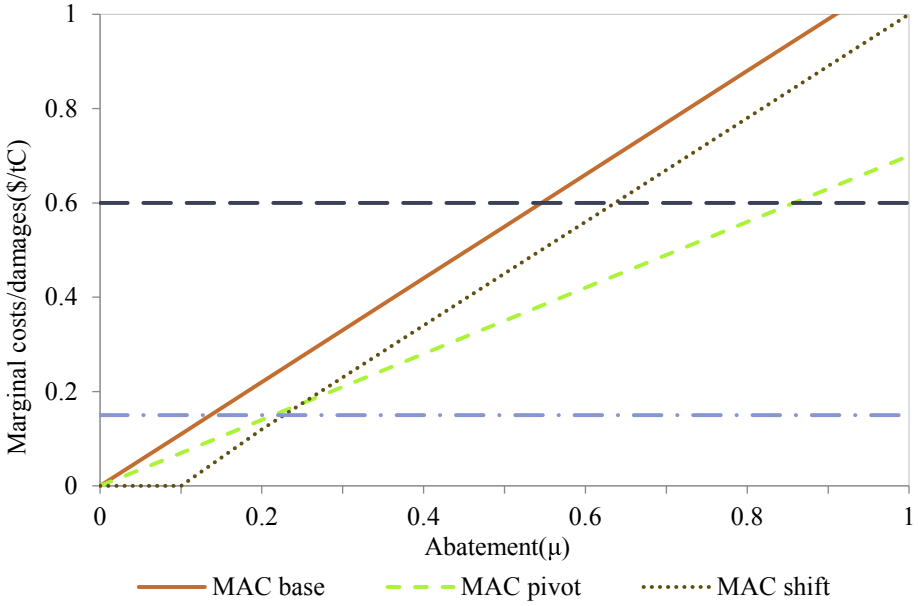

Fig. 2. Illustrative MAC curves and marginal damage curves.

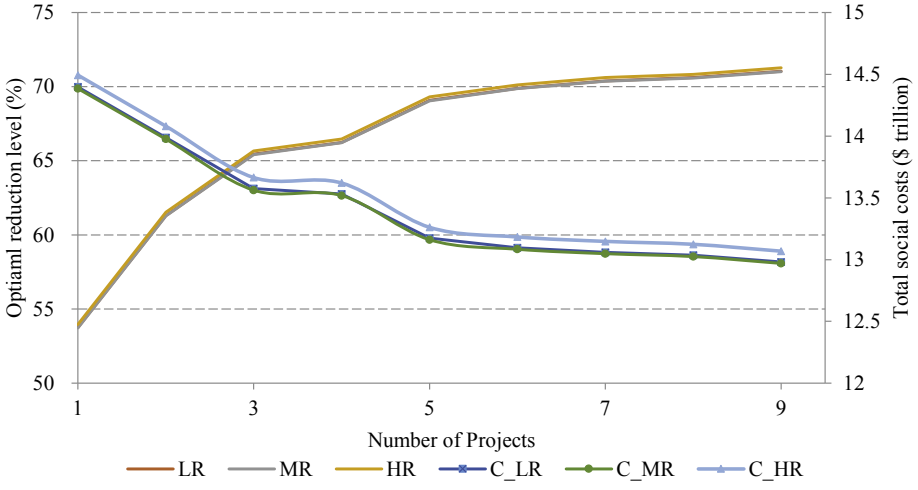

Fig. 3. Number of projects for optimal portfolio, level of abatement, and total social cost.

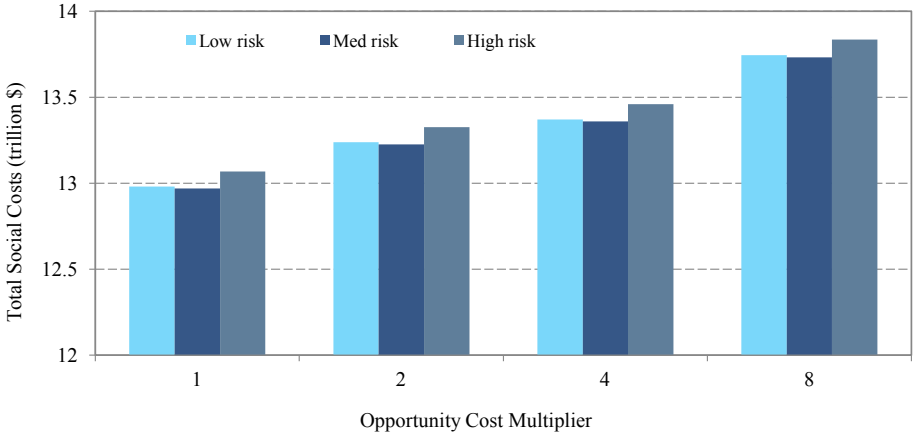

Fig. 4. Total social costs under different opportunity costs.

$$\alpha_{CSN} = 1 - \prod_i (1 - \alpha_i) \tag{2}$$

where $\alpha_i (i = C,\ S,\ N)$ represents the value of pivot for each technology; C, N, and S represent the CCS, nuclear, and solar PV technologies, respectively; and, α_{CSN} represents the pivot parameter of the combined technologies.

From Eq. (1), the MAC curve is used to acquire the abatement cost after the successful technological change by integrating μ. Namely, the primitive function of the MAC is:

$$C(\mu; \alpha, h) = (1 - \alpha)[C(\mu) - h\mu MAC(0.5)] \tag{3}$$

Taking combinations of technologies into account, the abatement cost function is formulated:

$$C(\mu; \alpha, h) = (1 - \alpha_{CSN})[C(\mu) - h\mu MAC(0.5)] \tag{4}$$

Based on the DICE 2007 (Nordhaus, 2008), the formulation of the baseline abatement cost function $C(\mu)$ is:

$$C(\mu) = b_0 \mu^{b_1} \tag{5}$$

where b_0 and b_1 are calibration parameters based on DICE 2007, $b_0 = 10.4$, $b_1 = 2.8$. Referring to Eq. (4) and Eq. (5), we can obtain the final abatement cost function:

$$C(\mu; \alpha, h) = (1 - \alpha_{CSN})\left[b_0 \mu^{b_1} - h\mu b_0 b_1 (0.5)^{b_1 - 1}\right] \tag{6}$$

2.3. The cost function of climate damage

Climate damage is one of the most important factors affecting emissions reductions and it is uncertain. Many previous studies have shown that the optimal level of investment in technologies depends on a probability distribution of climate damages (Baker and Adu-Bonnah, 2008; Baker et al., 2006). This study takes climate damage impact on the abatement cost into consideration. Based on (Nordhaus, 2008; Richard, 1995), the damage function is assumed to be quadratic:

$$D(\mu) = M_0 (Q - M_1 \mu)^2 \tag{7}$$

where $D(\mu)$ represents climate damage function. The stock of emissions in the atmosphere, Q, is set equal to the stock of emissions in 2185 under a business-as-usual (BAU) scenario in the DICE, namely, Q is equal to 2.5 trillion metric tons of carbon. M_0 and M_1 are calibration parameters. We cite the result, which Baker and Peng (2012) and Baker and Solak (2011) calculated based on relevant assumptions of DICE 2007, $M_0 = 2.74$, $M_1 = 0.597$.

Referring to Baker and Peng (2012) and Baker and Solak (2011) for the measurement of climate damage, we use random variable Z to represent climate damage uncertainty, then the climate damage cost function is as follow:

$$D(\mu; Z) = Z M_0 (Q - M_1 \mu)^2 \tag{8}$$

where $D(\mu; Z)$ represents the cost of climate damage under uncertainty. When random variable Z is realized, the variable μ is chosen, then the cost of climate damage is determined. Section 3.1.3 shows the details of the probability information of random variable Z.

2.4. Two stage stochastic programming model

2.4.1. A brief introduction of the model

Stochastic programming is developed from general mathematical programming. The aim of it is precisely to find an optimal decision in problems involving uncertain data (Birge and Francois, 2011). Given the difficulty of defining desirable decisions in a context of high future uncertainty, stochastic programming can be used to conduct a parametric analysis of hedging strategies (Labriet et al., 2012). In order to cope with the uncertainty of technological change and of climate change damage, a stochastic programming model is developed in this paper. However, the cost of abatement cannot be acquired until the R&D projects are determined. Thus, the stochastic programming model in our study has two stages.

The cost of abatement represented by Eq. (6), cannot be acquired until the R&D projects are determined. Therefore, the stochastic programming model has two stages. In the first stage, the decision is to determine which set of R&D projects to fund, represented by x. Then, the random variables α, h, and Z are realized. In the second stage, the decision is around how much to abate, represented by μ. Thus, the two-stage stochastic programming model is established. The objective function in terms of expectations is to minimize the abatement cost plus the climate damage cost:

$$E_{\alpha,h,Z}\left(\min_{\mu}[C(\mu; \alpha, h) + D(\mu; Z)]\right) \tag{9}$$

We let the indices i and j represent the technology categories (CCS, nuclear, and solar PV) and the specific project within the

category, respectively. For instance, $i = S,\ j = 1$ represents organic solar cells in solar PV. The index k represents the investment level; $k = 1,\ 2,\ 3$, denoting low, moderate, and high levels of investment, respectively. $x_{ijk} \in \{0, 1\}$ is the binary decision, x_{ijk} equals 1 if there is an investment in program ij at funding level k, and 0 otherwise.

In addition, only successful technological change can impact the MAC. Even if a technical project is invested in, it may fail. For instance, if we invest in the technology of pre-combustion carbon capture at a low funding level, its probability of success is only 1.7% — and more likely to fail. Thus, for each funded project ijk, there are two potential outcomes: failure or success. We index these by l; if $l = 1$, technological change is successful, and 0 otherwise. Then, we determine the probability of a combination of technologies. For example, the probability Pr of the event that we get success in post-combustion and no success in anything else, given there is high funding ($k = 3$) in post-combustion ($i = C, j = 3$):

$$Pr = p_{133,1} \prod_{(i,j,k) \neq (C,3,3)} p_{ijk,0} \tag{10}$$

where $p_{ijk,l}$ represents the probability that the funded project ijk will result in outcome l. However, the future breakthroughs of technologies are uncertain. We cannot use past data and relative frequencies to construct a probability distribution for the success of future breakthroughs. Therefore, the probability judgment around technological change is obtained by collecting expert elicitations. The details are presented in Section 3.1.2.

In addition, we assume that only the best technology project in each category will diffuse in the model. For example, if all CCS projects are successful, we will select the lowest cost project in the model. In other words, we take the parameter α [2] of this project in the model, only when:

$$\alpha_i(x) = \max_{j,k} \left(x_{ijk} \alpha_{ijkl} \right) \tag{11}$$

where α_{ijkl} represents the parameter α that funded project ijk and will result in outcome l. $\alpha_i(x)$ represents the selected parameter α in technology i.

Two separate but closely related two-stage stochastic programming models are considered: the BCM and the OOM. The details are as follows.

2.4.2. Budget constrained model

The BCM model is used to optimize the low-carbon energy technology R&D portfolios subject to a budget. The objective is to minimize the expected social cost by choosing the optimal R&D portfolio:

$$\min_x \left(E_{\alpha,h,Z} \left(\min_{\mu} [C(\mu; \alpha, h) + D(\mu; Z)] \right) \right) \tag{12}$$

subject to

$$\beta \sum_i \sum_j \sum_k f_{ijk} x_{ijk} \leq B \tag{13}$$

$$\sum_k x_{ijk} \leq 1 \quad \forall i, j \tag{14}$$

where f_{ijk} is the level of investment for funding level k of project ij; and B represents the R&D budget. β is an opportunity cost multiplier that reflects the value of opportunities forgone in favor of this R&D investment. Since there is a large opportunity cost for R&D funds, decision makers likely consider the value of the investment in technology R&D; thus, it is necessary to explore the impact of opportunity cost on the R&D technology portfolio. We show the results of the cases of total costs equal to 1, 2, 4, and 8 times the net costs based on Baker and Solak (2011).

The BCM model can easily and clearly explore the impact of different opportunity costs on the optimal R&D portfolio. However, subjected to the budget, the R&D of low-carbon technology is inhibited to some extent. Therefore, to optimize the R&D portfolio, we make the R&D budget a part of the objective function.

2.4.3. Overall optimal model

In the OOM model, the R&D budget is captured in the objective function. The purpose of the OOM model is not only to optimize the low-carbon technology R&D portfolio, but also to scale the R&D budget, which is an important difference from the BCM model. In practice, political constraints are likely to affect the choice of the budget; therefore, if the results of the R&D budget are not optimal, but the overall result is optimal or can capture the cause of this phenomenon, it is necessary to consider the OOM model. The equation is as follows:

$$\min_x \left(\sum_i \sum_j \sum_k f_{ijk} x_{ijk} + E_{\alpha,h,Z} \left(\min_{\mu} [C(\mu; \alpha, h) + D(\mu; Z)] \right) \right) \tag{15}$$

subject to

$$\sum_k x_{ijk} \leq 1 \quad \forall i, j \tag{16}$$

where x_{ijk} represents whether to invest in project ijk, which is the first stage decision variable.

3. Optimization of R&D in China's low-carbon energy technology

3.1. Data and parameters

3.1.1. The two effect parameters (α and h) of technological change on the MAC

Based on the characteristics of each technology project, two parameters are estimated by the GCAM. As the characteristics of the technology cannot be provided directly, we have to define what R&D results represent so called technological change success. Namely, defining the success of technological change is necessary. Baker and Solak (2011) give such a definition and then, divide the problem into small pieces for consulting experts so that relevant data can be acquired. According to the largest available potential, this study cites the relevant research results of α and h, which are listed in Table 2.

3.1.2. Technology R&D funding trajectories and probability information

Funding trajectories and probability information are also estimated by experts based on the definition of technological change

[2] This is a simplifying assumption that is derived from the GCAM. It has a very large number of technologies and technology categories. Therefore, any particular technology, such as solar PV, is modeled as a single technology, using a single set of parameter values.a.

Table 2
Pivot and shift for each technology.

Technology	CCS			Solar PV (c/kwh) [b]				Nuclear ($/kw) [c]				
	Pre-C	Oxy	Post-C	Org S		Thin S	Multi S	LWR	HTR		FBR	
Scenario [a]	–	–	–	5	3	5	2.9	1000	1500	1000	1500	1000
α	0.347	0.380	0.319	0.022	0.05	0.022	0.05	0.325	0.111	0.327	0.115	0.332
h	0.004	0.020	−0.008	0.007	0.017	0.007	0.017	0.118	0.028	0.111	0.029	0.115

[a] by referring the studies of Baker et al. (2008, 2009b)
[b] PV energy cost
[c] capital cost.

success. Baker et al. (2008) and (Baker et al., 2009a, b) set the R&D funding trajectories of technology from a global perspective. Furthermore, the countries they considered included China. Thus, their setting of funding years for R&D is still applicable in China. The specific funding years of each technology are shown in Table 3. The annual funding will vary depending on the level of R&D in different countries. However, in their study, US federal funding was the only support. Although China is the largest carbon emitter, its CCS technology lags behind the US, Australia, and the UK, among others. Therefore, China needs to vigorously develop CCS technology and equip facilities on a large scale (Global CCS Institute, 2016; IPCC, 2014). According to Kerr et al. (2009) and IEA and UNIDO (2011), the investment in CCS will jump to $15 trillion (R&D included). As a result, we increase China's investment in R&D for CCS technologies appropriately, as shown in Table 3.

In order to cope with the climate change problem and adjust the energy consumption structure, China plans to ramp up investment in relevant technology R&D and vigorously develop non-fossil fuels such as nuclear and solar PV (IEA, 2016). Based on new policy scenarios, between 2016 and 2040, $341 billion needs to be invested in China's nuclear technology, while the US only needs to invest $214 billion. At the same time, $328 billion needs to be invested in China's solar PV power generation, while the US only needs to invest $258 billion (IEA, 2015). Therefore, we appropriately increase China's annual funding in nuclear and solar PV. The fifth column in Table 3 shows the net present value, which is calculated based on a 5% real discount rate for different funding trajectories. It is worth noting that the probability information for the R&D funding trajectories is not the input data for calculating the values of α and h. Therefore, adjusting the funding trajectories and

Table 3
Technology R&D funding trajectories and probability distribution of technological change.

Technology	Project	Funding years (year)[a]	Annual funding (Million $)	NPV of funding (million $)[f]	Probability of success (%)[g]
CCS	Pre-C	10	6	46	1.7
			22	170	12.0
			55	425	25.3
	Oxy	10	0.8 or 6 [b]	24	5.2
			3 or 12 [c]	54	10.5
			6 and 12 [d]	75	17.8
	Post-C	15	6	62	59.0
			17–31 [e]	258	75.0
			53	550	80.5
Solar PV	Org S	10	16	124	0
					16.0
			80 (15years)	830	4.0
					26.8
	Thin S	10	7	54	29.7
			10	77	54.3
	Multi S	10	60	386	10.0
Nuclear	LWR	5	45	195	21.3
			65	281	33.8
			90	390	66.6
	HTR	10	110	849	0.5
					1.2
			210	1622	21.6
					10.0
			420	3243	40.2
					12.0
	FBR	10	155	1197	0.8
					9.0
			610	4710	1.0
					42.0
			1550	11969	20.3
					53.8

[a] The set of funding years is referred to Baker et al. (2008, 2009a, 2009b);
[b] The funding is $0.8 M/year in the first five years, while $6 M/year in the 2nd five years;
[c] The funding is $3 M/year in the first five years, while $12 M/year in the 2nd five years;
[d] The funding is $6 M/year in the first five years, while $12 M/year in the 2nd five years;
[e] $17 M/year for the first year, ramping up at an even rate to $31 M/year in the last year;
[f] The net present value is calculated at 5% real discount rate for each technology funding trajectory;
[g] See Appendix for probability information.

the probability information will not affect the values of α and h.

On the basis of the given R&D funding trajectories, we average the probability information collected from consulting technical experts, policymakers, and academics. Subsequently, we establish the probability distribution information for technological change. See Appendix for details.

3.1.3. Probability distribution of climate damage

Referring to Nordhaus (1994), the probability distribution of climate damage is shown in Table 4. In each risk case, there are two possible realizations for the damage random variable Z: either Z_h or Z_l. These represent a high or low level of damage risk, respectively. We assume $Z_l = 0$, and Z_h have three possible values, 1, 3, and 14.6. The last row in Table 4 shows the optimal level of abatement when $Z = Z_h$ and there is no technological change. Specifically, this value is $\mu^*(Z_h)$ where:

$$\mu^*(Z_h) \equiv \arg\min_{\mu \le 1} [C(\mu; \alpha, h) + D(\mu; Z)] \tag{17}$$

3.2. Solving the proposed model

The two-stage stochastic programming model established involves two sets of decision variables. x_{ijk} (indicates whether to invest in project ijk) and μ (level of abatement). However, the two sets of decision variables cannot be calculated at the same time. Furthermore, there are a large number of possible portfolios, and various portfolios have different complexities in solving the expected value of abatement costs. Thus, it is difficult to solve the model. For example, when only one project is selected in the portfolio, the expectation of the abatement cost is equal to the value of the probability of technological change, multiplying corresponding α. When two projects are involved, four cases exist, and if nine projects are involved, there are 512 cases. Similarly, almost every project has its own funding level, and there are over 73,000 possible portfolios. The key here is that only one α can be chosen when several projects in one technology are selected. At that time, we need to measure the investment amount for each project and the probability of technological change. Hence, the general solution of stochastic programming is no longer suitable to solve this model. Although Monte Carlo simulation and intelligent optimization algorithms, such as the genetic algorithm, can be applied to solve this kind of problem effectively, the processes are difficult and complicated (Baker and Peng, 2012). Relying on the greedy algorithm (Baker and Solak, 2011), we apply mixed integer nonlinear programming with constraints (MINLPc) to solve the model.

In the OOM model, beginning with only one project, we then expand it to all nine projects. Therefore, we calculate the mathematical expectation by dividing the technology portfolios into nine types. In the calculations for the first three types we list all the results, and then introduce them into the latter calculations for the other six types. In the BCM model, we set up a few R&D budgets and then optimize the portfolio for each budget. Furthermore, both models are associated with the probability distribution of climate damage. Moreover, we apply the MINLPc and optimize each situation by using the MIDACO solver in Matlab. It is worth noting that when two or more projects are chosen in a technology, we choose α by comparing the ratios of probability of technological change to the amount of the corresponding investment. In order to ensure the reliability of the results when that ratio is approximate, all the results in every situation are calculated.

Table 4
Probability distribution of climate damage.

Risk level	Low risk	Medium risk	High risk
Z_h	1	3	14.6
$P[Z = 0]$	0	0.667	0.931
$P[Z = Z_h]$	1	0.333	0.069
μ^* if $Z = Z_h$	46%	80%	100%

4. Results and discussion

1) The results of both models show that the combination of an optimal low-carbon technology R&D investment portfolio is robust to different climate damage risks. Take the OOM model, for example. Although the nine low-carbon technology projects have a total of 73,728 different possible portfolios under three climate damage risk levels (high, medium, and low), considering such risks, the optimal choice of technology remains unchanged, as shown in Table 5. When only one project is selected, the optimal project is Post-C under different damage risk levels. At the same time, the optimal portfolio contains Post-C, LWR, and HTR when three projects are selected. This indicates that a combined optimal portfolio has a strong robustness to climate damage risks. This is mainly because, in the two models here, the impact of technological change plays a greater role than climate damage risk. Compared to the technology portfolios containing seven projects, those with eight projects only add the organic solar cell, which has a low success probability for technological change and little impact on abatement costs ($\alpha = 0.022$). Yet, it still drives the total social cost to a further decline. However, the three climate damage risks do not change this result, which is consistent with the results of Baker and Peng (2012) and Barron et al. (2014).

Even considering the distribution of climate damage based on Nordhaus (1994), the results of expert and related actual data indicate that technological change achieved by investing in R&D has a significant impact. Focusing on the effects of technological change rather than climate damage risk is more in line with China's actual needs to achieve abatement targets. Moreover, in all the optimal technology R&D portfolios, Post-C is an indispensable technology project. This is mainly because Post-C achieves a higher level of abatement and lower expected total social costs. Further, its value of α is 0.319 (the higher the value of α, the faster the drop in the cost of emissions reduction) and the probability of technological change success (59%–85%) is higher than the other technologies. As a result, Post-C is an indispensable technology project in the optimization results.

2) The optimal technology R&D portfolio varies under different opportunity costs, but, for the three technologies, projects for each technology are always involved. The optimal technology R&D portfolio under four different opportunity cost multipliers and different climate damage risk levels are shown in Table 6. Giving a total budget constraint, we can see which technology projects receive less funding or exit the optimal portfolio as the opportunity cost increases, especially for some nuclear technology projects. Thus, the amount of investment required for nuclear technology is very large, up to $12 billion. While for other technologies, such as for organic solar cells, the maximum amount of investment is less than $0.90 billion. In other words, when the opportunity cost increases, decision makers begin to measure the benefits of the investment and, to a certain extent, abandon technology projects that demand large funds. However, regardless of the change in the opportunity cost and the damage risk, the optimal portfolio includes all three low-carbon

Table 5
Optimal investment decision for all levels of climate damage risk.

Number of projects	Investments decision								
	CCS			Nuclear			Solar PV		
	Pre-C	Oxy	Post-C	LWR	HTR	FBR	Org S	Thin S	Multi S
1	–	–	✓	–	–	–	–	–	–
2	–	–	✓	✓	–	–	–	–	–
3	–	–	✓	✓	✓	–	–	–	–
4	✓	–	✓	✓	✓	–	–	–	–
5	✓	-	✓	✓	✓	✓	–	–	–
6	✓	✓	✓	✓	✓	✓	–	–	–
7	✓	✓	✓	✓	✓	✓	–	✓	–
8	✓	✓	✓	✓	✓	✓	✓	✓	–
9	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 6
Optimal R&D investment portfolio under different opportunity cost multipliers.

β	Risk level	Investments ($ billion)									Total Investment ($ billion)	μ^* (%)	Expected social cost ($ trillion)
		CCS			Nuclear			Solar PV					
		Pre-C	Oxy	Post-C	LWR	HTR	FBR	Org S	Thin S	Multi S			
1	L	0.43	0.08	0.55	0.39	3.24	12.00	0.83	0.08	0.39	17.95	71.0	12.96
	M	0.43	0.08	0.55	0.39	3.24	12.00	0.83	0.08	0.39	17.95	71.0	12.95
	H	0.43	0.08	0.55	0.39	3.24	12.00	0.83	0.08	0.39	17.95	71.3	13.05
2	L	0.43	0.08	0.55	0.39	3.24	4.71	0.12	0.08	0.39	9.98	69.2	13.23
	M	0.43	0.08	0.55	0.39	3.24	4.71	0.12	0.08	0.39	9.98	69.2	13.22
	H	0.43	0.08	0.55	0.39	3.24	4.71	0.12	0.08	0.39	9.98	69.4	13.32
4	L	0.43	0.08	0.55	0.39	1.62	0	0.83	0.08	0.39	4.36	67.4	13.37
	M	0.43	0.08	0.55	0.39	1.62	0	0.83	0.08	0.39	4.36	67.4	13.35
	H	0.43	0.08	0.55	0.39	1.62	0	0.83	0.08	0.39	4.36	67.6	13.46
8	L	0.43	0.08	0.55	0.39	0	0	0.12	0.08	0.39	2.03	64.2	13.74
	M	0.43	0.08	0.55	0.39	0	0	0.12	0.08	0.39	2.03	64.1	13.73
	H	0.43	0.08	0.55	0.39	0	0	0.12	0.08	0.39	2.03	64.4	13.83

technologies. For example, when the opportunity cost multiplier reaches eight, even if the organic solar cell project receives less funding, nuclear technology projects, such as LWR, are still retained. Since, for CCS and nuclear, the probability of success in technological change is relatively high, the impact on the abatement cost is also relatively large (α is large). Thus, they can always be a part of the optimal R&D portfolio. In addition, in the BCM model with large budget constraints, the small amount of investment required by solar PV always makes it attractive in the portfolio.

3) Regardless of the level of damage risk, the number of projects in the optimal portfolio is proportional to the abatement level and inversely proportional to the total social costs. According to the OOM model, under different climate damage risks, with an increasing number of technology projects, the optimal abatement increases. In contrast, the total social cost decreases. If only one project is selected, the optimal project is Post-C. In the medium risk case, the optimal level of abatement is about 53.7%, and the total cost is about $14.40 trillion, as shown in Fig. 3. However, when all projects are selected, the optimal level of abatement rises to 71.0% or more, and the total cost is reduced to below $12.97 trillion. The decrease in total costs is mainly due to the fact that successful technological changes reduce the cost of achieving higher levels of abatement.

In addition, with an increasing number of technical projects, the parameter α_{CSN} increases, contributing to a decrease in the expectation of abatement costs, and the total social cost decreases consequently. These results indicate that low-carbon technology synergistic R&D strategies can achieve better results. For the same optimal R&D portfolio, the total social cost (C_HR) in the high risk case is slightly higher than in low risk case and the medium risk case by 0.7%–0.8%. However, the optimal level of abatement shows little difference under the different damage risk scenarios. Yet, the climate damage risks can affect the total social costs to some extent. The model established here is to minimize the total social cost, so when the climate damage risk is high, it is necessary to consider whether to invest or further invest in the identified R&D portfolio.

4) No matter how large the opportunity cost is, the total social cost is lowest under medium risk of climate damage. On the one hand, although under different damage risks, the optimal technology R&D investment portfolios do not change for each opportunity cost multiplier, there is a certain gap in the total social cost. On the other hand, total social costs increase as opportunity costs increase; however, it is lowest at medium risk of climate damage. As shown in Fig. 4, when the opportunity cost multiplier is one, the total social cost under medium risk is $12.97 billion, lower than the $12.98 billion under low risk and $13.07 billion under high risk. The reason is that the cost of climate damage is proportional to the expected value of climate damage. Under three damage risks, the corresponding expectation of medium climate damage risk random variables ($Z = 3$) is 0.999, which is lower than (1 and 1.0074, respectively) the low and high climate damage risk random variables (Z is 1 and 14.6, respectively). Lower climate damage costs also reduce total social costs.

As the opportunity cost increases, the total social costs are increasing under different risks. Since the fact that the maximum abatement level and the minimum total social costs can be achieved when all the technology projects are selected. However, as

the opportunity cost increases, some technology projects leave the portfolio. Therefore, the corresponding abatement level reduces and the total social costs increase. In addition, although the investment portfolio under the different opportunity costs remains unchanged, MR is still the lowest in the same portfolio even if the total social costs increase.

5. Conclusions and policy recommendation

5.1. Conclusions

In order to respond actively to global climate change and meet China's carbon emissions reduction targets efficiently, taking into account China's economic and technology levels, this study established a two-stage stochastic programming model. Then, the optimal R&D technology portfolio for three low-carbon energy technologies (CCS, solar PV, and nuclear), including nine projects, was optimized. Utilizing expert input, the model captured both uncertainty of technological change and climate change damage. According to the optimization results, the following conclusions can be drawn:

1) Different climate damage risks do not affect the optimal R&D technology investment decision. In this study, three low-carbon technologies and three climate damage risk levels were considered. However, the optimal R&D portfolio remained unchanged and was robust under the different damage risk levels.
2) The optimal technology R&D portfolio varied under different opportunity cost scenarios; however, for the three technologies, projects for each technology were always involved. As the opportunity cost multiplier increased with the total amount of investment constraint, some technologies requiring higher funding, for example, FBR exit the optimal portfolio. However, the nuclear energy projects are not abandoned in total because a higher abatement level can be achieved by investing in some of these.
3) Under medium risk of climate damage, the total social cost is lowest in the optimal R&D portfolio. Although it increases as the opportunity costs increase, the total social cost is still lowest at medium damage risk, since the expectation of medium damage risk is the lowest among the three damage risk cases.
4) Synergistic R&D strategies for different technologies are conducive to enhancing the level of CO_2 abatement as well as for reducing the total social cost of abatement. The number of projects in the optimal R&D portfolio is proportional to the abatement level and inversely proportional to the total social cost. As the number of projects included in the optimal R&D portfolio increased, the expected level of abatement increased accordingly. However, the successful technological change reduced the costs of achieving higher abatement levels. Moreover, as the number of technologies increased, the total expectation of technological change became slightly smaller, and thus, no longer conducive to reducing the total social cost of abatement.

5.2. Policy recommendation

According to the results of the present study, we propose the following policy implications for making China's low-carbon energy technology R&D investment decision:

1) The level of climate damage risk should not be an important basis for decision-making when China is formulating its R & D investment strategy for low-carbon energy technologies. Climate damage risk level has no substantial impact on optimal technology R&D portfolio. Therefore, when making technology R&D investment decisions, the climate damage risk level should not be considered, but the R&D potential of technology and the level of corresponding investment in R&D and other factors should be taken into account. For instance, crystalline silicon solar cells technology has become saturated, and it has small R&D potential, so it is difficult to achieve technological change even if invest a large amount funding. However, technology such as High temperature reactors has greater R&D potential, but it requires a high level of investment.
2) China needs to strengthen the R&D level of nuclear technology. According to the conclusions of this paper, no matter how much opportunity cost is, the nuclear technology is always included in the optimal R&D portfolios. As a result of the security issue, the development of nuclear power in the world has been hindered since the nuclear accident in Fukushima, Japan. But, as a big energy consuming country with small nuclear power consumption, it is imperative to invest R&D of nuclear power technology, especially Light water reactors in China.
3) Various low-carbon energy technologies should be researched and developed synergistically. The basic purpose of low-carbon energy technology R&D is to reduce the negative impact on the environment caused by the large-scale use of fossil energy, and promote global green sustainable development. Synergistic R&D strategies for different technologies are conducive to enhancing the level of CO_2 abatement as well as reducing the total social cost of abatement. Thus, we should not emphasize on one particular technology merely and ignore the others; the technologies should be researched and developed congruously and jointly.

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Appendix

Nomenclature

Indices

i	Index of technologies, i=(Solar PV, CCS, Nuclear)
j	Index of projects within each technology (See Table 1)
k	Index of funding levels, k=(low, medium, high)
l	Technology change outcomes for each funding project j of technology i at funding level k

Parameters

α	Pivoting effect on the marginal cost of abatement
h	Shifting effect on the marginal cost of abatement
α_{CSN}	Pivot of the combined technologies
b_0, b_1	Parameters of the abatement cost function
Z	Stochastic damage risk multiplier
M_0, M_1	Parameters of the damage cost function
Q	Baseline stock of emissions
$p_{ijk,l}$	Probability of the funded project ijk will result in outcome l
Pr	Probability of the funded portfolio of technologies
β	Opportunity cost multiplier
B	R&D Budget
f_{ijk}	Cost of funding project j of technology i at level k

Model Variables

MAC	Marginal abatement cost
$\overline{MAC}$	Marginal abatement cost after successful technological change
C	Cost of abatement
D	Cost of climate damage
μ	Level of abatement (decision variables)
x_{ijk}	Binary decision variable corresponding to funding project j of technology i at funding level k(decision variables)

Probability information of technological change of each technology project given by experts

Four of different background experts been consulted to obtain probability information. The first one is a researcher for low-carbon energy technology in university; the second one is a developer on low-carbon technologies for the enterprise; the third one is a reputable energy economist is and the last one is a government official in charge of technology R&D policy. The details are list from Tables A1–A9.

Table A1
CCS—Pre-combustion.

Funding trajectory	$6 M/yr over 10years				$22 M/yr over 10years				$55 M/yr over 10years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.03	0.01	0.02	0.008	0.20	0.09	0.12	0.07	0.49	0.18	0.27	0.07
Average of probabilities	0.017				0.120				0.253			

Table A2
CCS—Oxyfuel.

Funding trajectory	$0.8 M to $6 M				$3 M to $12 M				$6 M to $12 M			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.09	0.04	0.07	0.008	0.20	0.10	0.08	0.04	0.30	0.22	0.18	0.012
Average of probabilities	0.052				0.105				0.178			

Table A3
CCS—Post-combustion.

Funding trajectory	$6 M/yr over 15years				$17 M/yr ramping up to $31 M (15 years total)				$53 M/yr over 15years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.90	0.60	0.26	0.60	1	0.90	0.40	0.7	1	1	0.50	0.72
Average of probabilities	0.59				0.75				0.805			

Table A4
Solar PV—Organic.

Funding trajectory	$16 M/yr over 10years				$80 M/yr over 15years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0	0	0	0	0.08	0.01	0.05	0.02
PV energy cost = 3c/kwh								
Average of probabilities	0				0.04			
Probability	0.35	0.07	0.13	0.09	0.48	0.12	0.34	0.13
PV energy cost = 5c/kwh								
Average of probabilities	0.16				0.268			

Table A5
Solar PV—Thin film.

Funding trajectory	$7 M/yr over 10years				$10 M/yr over 10years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.40	0.30	0.28	0.208	0.80	0.65	0.50	0.22
Average of probabilities	0.297				0.543			

Table A6
Solar PV—Multi-junction.

Funding trajectory	$60 M/yr over 10years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.20	0.05	0.10	0.05
Average of probabilities	0.10			

Table A7
Nuclear—LWR.

Funding trajectory	$45 M/yr over 5years				$65 M/yr over 5years				$90 M/yr over 5years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability	0.1	0.15	0.5	0.1	0.2	0.3	0.55	0.3	0.34	0.805	0.90	0.62
Average of probabilities	0.213				0.338				0.666			

Table A8
Nuclear—HTR.

Funding trajectory	$110 M/yr over 10years				$210 M/yr over 10years				$420 M/yr over 10years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability capital cost = 1000$/kW	0	0	0.02	0	0.08	0.12	0.52	0.142	0.15	0.30	0.65	0.506
Average of probabilities	0.005				0.216				0.402			
Probability capital cost = 1500$/kW	0	0.01	0.3	0.008	0	0.10	0.35	0.05	0.08	0.1	0.3	0.1
Average of probabilities	0.012				0.10				0.12			

Table A9
Nuclear—FBR.

Funding trajectory	$155 M/yr over 10years				$610 M/yr over 10years				$1550 M/yr over 10years			
Expert	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 1	Ex. 2	Ex. 3	Ex. 4
Probability capital cost = 1000$/kW	0	0.01	0.022	0	0	0.01	0.03	0	0.10	0.21	0.40	0.10
Average of probabilities	0.008				0.010				0.203			
Probability cost = 1500$/kW	0.06	0.10	0.20	0	0.24	0.60	0.70	0.14	0.45	0.70	0.85	0.15
Average of probabilities	0.090				0.42				0.538			

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